



ROBINSON BOWMAKER PAUL



AUSTRALIAN ENERGY MARKET OPERATOR

REPORT: 2018 ASSESSMENT OF SYSTEM RELIABILITY

(EXPECTED UNSERVED ENERGY), DEVELOPMENT OF

AVAILABILITY CURVE AND DSM DISPATCH QUANTITY

FORECASTS FOR THE SWIS

1 JUNE 2018

Prepared by: Sue Paul
Richard Bowmaker

Document version: FINAL 1.0

Robinson Bowmaker Paul
PO Box 10280
The Terrace
Wellington 6143
New Zealand

www.robinsonbowmakerpaul.com

EXECUTIVE SUMMARY

Australian Energy Market Operator (AEMO) has engaged Robinson Bowmaker Paul (RBP) to:

- Undertake the Reliability Assessment and Development of the Availability Curve for the Southwest Interconnected System (SWIS)
- Forecast the Expected DSM Dispatch Quantity (EDDQ) in accordance with clause 4.15.4A of the Wholesale Electricity Market (WEM) Rules and the Market Procedure: *Determination of the Expected DSM Dispatch Quantity and the DSM Activation Price*.

This report contains the details and results of our analysis.

CONTEXT

AEMO is responsible for operating a Reserve Capacity Mechanism (RCM) to ensure that adequate supply is available over the long term. To assess the amount of reserve capacity that will be required the AEMO undertakes a Long-term Projected Assessment of System Adequacy (Long Term PASA). The results of the Long Term PASA analysis feed into the AEMO's Statement of Opportunities (SOO) report which forecasts:

- The Reserve Capacity Target (RCT) (WEM Rule (MR) 4.5.10(b)) for each Capacity Year in the Long Term PASA study and the Reserve Capacity Requirement (MR 4.6.1). The RCT is set so as to meet the Planning Criterion which is defined in MR 4.5.9 and comprises two components:
 - A forecast peak component to ensure that adequate supply is available to meet a one in ten-year peak (MR 4.5.9(a)) plus a reserve margin¹ (including transmission losses, allowing for intermittent loads) while maintaining frequency keeping capacity requirements.
 - A reliability component to ensure expected energy shortfalls are limited to 0.002% of annual demand (MR 4.5.9(b)).
- Generation capacity and Demand Side Management (DSM) requirements in the form of the Availability Curve, which is defined by MR 4.5.12.

¹ The reserve margin is calculated as the greater of 7.6% of the 10% POE demand forecast, and the largest generating unit in the SWIS.

Additionally, MR 4.5.14A and 4.5.13(h) require AEMO to calculate and publish the Expected DSM Dispatch Quantity (EDDQ) for each Capacity Year in the Long Term PASA study.

The purpose of this exercise is to:

- Undertake a Reliability Assessment to ensure the RCT is compliant with MR 4.5.9(b)
- Develop the Availability Curve defined by MR 4.5.12
- Forecast the EDDQ defined by MR 4.5.14A.

SCOPE

Our modelling covers:

- The Reliability Assessment for the 2018 Reserve Capacity Cycle covering Capacity Years 2018/19 to 2027/28
- The Availability Curve for the second and third year of the relevant Reserve Capacity Cycle, namely 2019/20 and 2020/21
- The forecasted EDDQ for Capacity Years 2018/19 to 2027/28.

METHODOLOGY

There are four components to the analysis undertaken in this report:

- Developing forecasted load duration curves (LDC) for each Capacity Year in the Long Term PASA Study Horizon (given a 50% POE peak forecast and an annual demand forecast)
- Performing the Reliability Assessment by undertaking probabilistic simulations of the Wholesale Electricity Market
- Developing the Availability Curve
- Forecasting the EDDQ.

Each component is described further below.

Development of Load Duration Curves

Load duration curves (or LDCs) are forecasted by:

- First developing a base-year LDC averaging historical data over the past five years and

- Second, scaling the base year LDC up to match both the 50% peak forecast and the total expected demand in each Capacity Year².

For more details on our load development methodology refer to Section 2.2.

Reliability Assessment

The Reliability Assessment is undertaken using a combination of fundamental market modelling and Monte Carlo analysis.

In brief, using the forecasted LDCs developed above, the WEM is simulated (using random load and forced outages). The probabilistic simulations were then used to derive the expected unserved energy (EUE), and to check that the EUE was less than or equal to 0.002% as a proportion of annual demand (as required by MR 4.5.9(b)).

For more details on our market modelling methodology refer to Section 2.3.

Availability Curve

The Availability Curve is developed in accordance with MR 4.5.10(e), MR 4.5.12(b) and MR 4.5.12(c) by:

- Developing a two-dimensional duration curve of the forecast minimum capacity requirements (MR 4.5.10(e)). This is undertaken by scaling the base year LDC up to the relevant forecast peak and demand quantity (consistent with MR 4.5.10(e)(i)), and then adding the Reserve Margin and Load Following Ancillary Services requirement (as required by MR 4.5.10(e)(ii)).
- Forecasting the minimum capacity (Availability Class 1) required such that if all available DSM (Availability Class 2) were activated and System Management's outage evaluation criteria (as defined in MR 3.18.11) were to apply, then the Planning Criterion would still be met (MR 4.5.12(b)). This is undertaken by repeating the modelling exercise described above with four differences:
 - First, DSM is modelled in greater detail to take into account the constraints around the availability of DSM facilities. We have allocated DSM throughout the year using an optimisation model that dispatches DSM so as to minimise the peak and subject to

² Peak and energy demand forecasts are provided by AEMO.

scheduling and availability constraints. See Section 2.4.1 for further details on our approach to modelling DSM.

- Second, we have specified a Reserve Requirement of 520 MW³ in the market model to represent the Ancillary Services requirement of MR 3.18.11A (i.e. the Ready Reserve Standard). This will ensure that there is always a capacity margin of 520 MW in any given hour.
- Third, forced outages are taken out of the model, and the only stochastic component of the simulation is random load. The reason for the removal of forced outages is that the specification of a 520 MW reserve requirement on top of forced outages effectively over-estimates the capacity margin. The purpose of the 520 MW margin is to cover unforeseen events such as forced outages. As such, if there were a forced outage in a given period, the operating reserve would be used to generate to prevent unserved energy. Hence, including forced outages and maintaining the 520 MW capacity margin (for reserve only) could lead to EUE exceeding 0.002% of annual demand.
- Finally, for each Capacity Year of the relevant Reserve Capacity Cycle, we iterate the model so as to reallocate the amount of DSM and generating capacity (keeping the total capacity capped at the RCT level) until the EUE requirement in MR 4.5.9(b) was violated.
- The level of generation capacity at which the EUE equals 0.002% of expected demand sets the minimum capacity prescribed in MR 4.5.12(b).
- Deriving the capacity associated with Availability Class 2 (as defined in MR 4.5.12(c)).

For more details on the development of the Availability Curve refer to Section 2.4.

EDDQ

We have forecasted the EDDQ using the following approach:

- **Forecast EUE when DSM is dispatched for zero hours ($EUE_{t,0}$).** This involves repeating the Reliability Assessment as described above but setting the available capacity of all DSM facilities to zero. Hence, only generation capacity is available to meet demand as described in MR 4.5.14C(a).
- **Forecast EUE when DSM is dispatched for 200 hours ($EUE_{t,200}$).** This involves repeating the Step 1 above but with the forecasted LDC adjusted to take into account DSM dispatch for exactly 200 hours. The optimised DSM dispatch is deducted off the forecasted LDC, and it is this adjusted

³ Source: AEMO.

LDC that becomes an input into the market model. Hence, generation capacity plus exactly 200 hours of DSM dispatch is available to meet demand as described in MR 4.5.14C(b).

- Calculate EDDQ in year t as follows:

$$EDDQ_t = \frac{EUE_{t,0} - EUE_{t,200}}{\text{Expected DSM Capacity Credits}_t}$$

RESULTS

Reliability Assessment

The Reliability Assessment indicated that for all Capacity Years of the Long Term PASA Study Horizon (2018/19 to 2027/28) the RCTs are expected to be set by the forecast peak quantity determined by MR 4.5.9(a).

The EUE as a percentage of annual demand when total capacity is capped at the forecast peak component given by MR 4.5.9(a) (first column) is summarised in Table 1. Here we see that the peak forecast component is sufficient to limit expected energy shortfalls to 0.002% of annual demand in all years⁴.

Table 1. Results of reliability assessment

Capacity Year	10% POE + Reserve Margin + LFAS requirement + IL allowance	50% POE Peak Load (MW)	Expected demand (MWh)	EUE (MWh)	EUE as % of load
2018/19	4,553	3,909	18,304,209	8.1402	0.0000445%
2019/20	4,559	3,914	18,325,939	0.0000	0.0000000%
2020/21	4,581	3,928	18,416,128	0.0000	0.0000000%
2021/22	4,600	3,951	18,549,476	0.0635	0.0000003%
2022/23	4,626	3,983	18,707,347	2.5368	0.0000136%

⁴ Note that the 2018/19 and 2019/20 values in Table 1 do not replace the respective RCTs set in the 2017 WEM SOO.

Capacity Year	10% POE + Reserve Margin + LFAS requirement + IL allowance	50% POE Peak Load (MW)	Expected demand (MWh)	EUE (MWh)	EUE as % of load
2023/24	4,649	3,999	18,871,983	0.0617	0.0000003%
2024/25	4,677	4,024	19,096,597	0.9467	0.0000050%
2025/26	4,700	4,056	19,351,194	0.0000	0.0000000%
2026/27	4,730	4,082	19,641,783	0.0000	0.0000000%
2027/28	4,773	4,113	19,961,251	0.0126	0.0000001%

The highest unserved energy occurs in 2018/19 (although EUE as a percentage of expected demand is well short of 0.002%). The unserved energy in 2018/19 is a result of 200MW of thermal plants that are expected to be on outage in the first two weeks of August 2019⁵. Due to recent changes in load shape, there are now some high load periods in winter months. The combination of planned outages and high winter load result in unserved energy in August 2019.

Availability Curve

The Availability Curves for Capacity Years 2019/20 and 2020/21 are summarised in Table 2 below. The load duration curves used to estimate MR 4.5.10(e) are illustrated in Figure 1 and Figure 2.

Table 2: Availability Curve, 2019/20 - 2020/21.

	2019/20	2020/21
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1		
Minimum capacity	3,919	3,946
MR 4.5.12(c): Capacity associated with Availability Class 2		
DSM	640	635

⁵ Based on information provided by market participants under MR 4.5.3.

Figure 1: Forecast capacity required, 2019/20

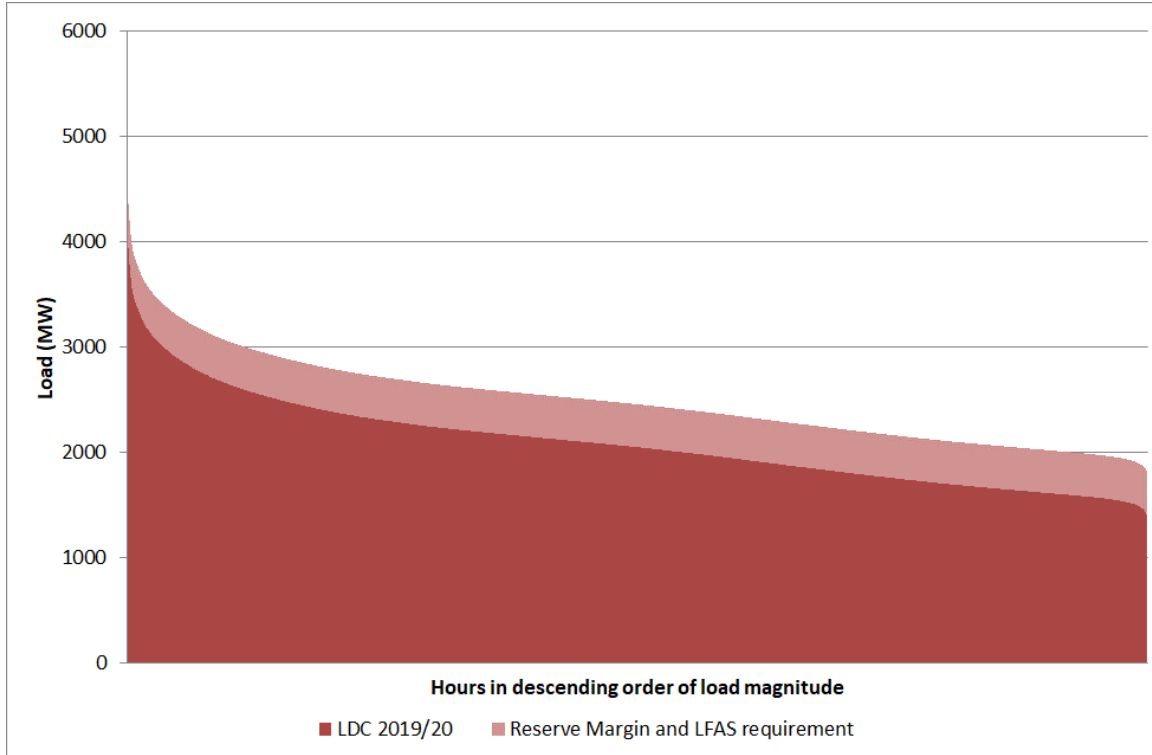


Figure 2: Forecast capacity required, 2020/21

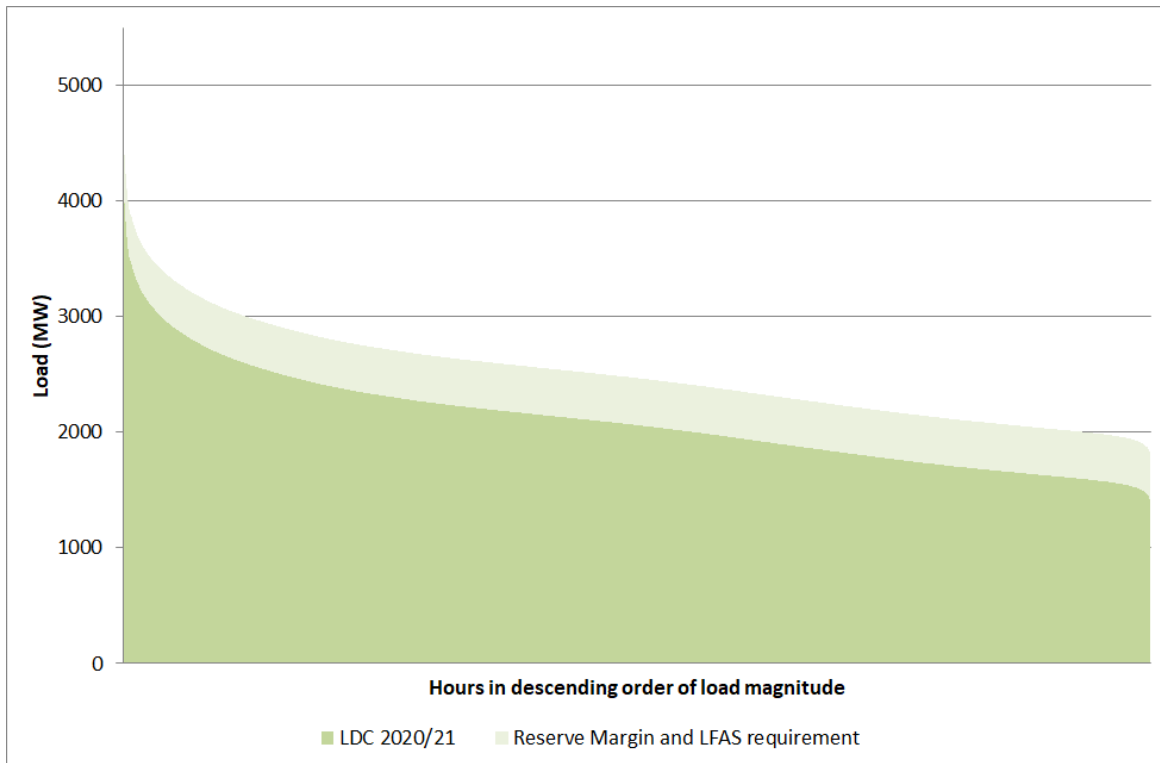


Table 7 in Section 3.2 compares the Availability Curve derived for the 2017 Long Term PASA to the current (Long Term PASA 2018) results. The capacity associated with Availability Class 2 (MR 4.5.12(c)) has decreased by 197MW since last year’s Long Term PASA from 837MW to 640MW. This decrease is driven by:

- 900MW of thermal plants expected to be on outage in the first two weeks of October 2019⁶.
- The DSM optimisation model allocating hourly DSM to minimise the peak⁷ subject to availability constraints. This means that most of the DSM is dispatched in the peakiest part of the LDC which occurs in the summer months (with some intervals in winter due to changing load shape). The model dispatches lower levels of DSM in October 2019 which is not enough to meet the net load with 900MW of scheduled generation on outage.
- The increased amount of solar in the capacity stack which means that in the evening (non-daylight) hours in October the amount of available generation decreases further.

Note that while the RCT values in the 2018 Long Term PASA have decreased (compared with what was published in the 2017 Long Term PASA), this is not a driver for the decrease in the capacity associated with Availability Class 2. This is because, the decrease in the RCT has been offset by a corresponding decrease in peak and energy demand forecasts.

Expected DSM Dispatch Quantity (EDDQ)

The EDDQ results are summarised in Table 3. This also provides the resulting DSM Reserve Capacity Price (RCP) assuming an interim DSM Activation Price of \$33,460⁸.

Table 3. EDDQ results

Capacity Year	EUE(t,0)	EUE(t,200)	CC(t)	EDDQ(t)	DSM RCP based on \$33,460 DSM Activation Price (MR 4.5.14F)
2018/19	19.9845	8.1402	57.426	0.2063	\$23,631.25
2019/20	0.9484	0.0000	66	0.0144	\$17,210.81
2020/21	0.0000	0.0000	66	0.0000	\$16,730.00

⁶ Based on information provided by market participants under MR 4.5.3.

⁷ In accordance with MR 4.5.12(b), the DSM optimisation model dispatches DSM facilities to minimise peak demand throughout the year (as opposed to maximising the operating reserve margin).

⁸ As specified in Market Rule 4.5.14F; the DSM Activation Price represents the Value of Lost Load (VoLL).

Capacity Year	EUE(t,0)	EUE(t,200)	CC(t)	EDDQ(t)	DSM RCP based on \$33,460 DSM Activation Price (MR 4.5.14F)
2021/22	0.8142	0.0635	66	0.0114	\$17,110.62
2022/23	4.8489	2.5368	66	0.0350	\$17,902.16
2023/24	0.5860	0.0617	66	0.0079	\$16,995.78
2024/25	2.3021	0.9467	66	0.0205	\$17,417.10
2025/26	0.1106	0.0000	66	0.0017	\$16,786.08
2026/27	0.0341	0.0000	66	0.0005	\$16,747.30
2027/28	1.1613	0.0126	66	0.0174	\$17,312.38

The highest EDDQ occurs as a result of 200MW of scheduled generation expected to be on outage in the first two weeks of August 2019 combined with changing load shape leading to higher load periods in winter months (see above).

EDDQ is otherwise low in most years. The reason is that unserved energy is very low under the reliability scenario (see Table 5). This, combined with the fact that there are only two DSM facilities⁹ means that not running these DSPs has a minimal impact on unserved energy.

⁹ With a combined Capacity Credit assignment of 57.426 MW in 2018/19 and 66 MW in other LT PASA years.

CONTENTS

EXECUTIVE SUMMARY.....	3
1 INTRODUCTION.....	14
1.1 Context.....	14
1.2 Scope of Modelling	15
1.3 Structure of this report	15
2 METHODOLOGY	16
2.1 Overview of modelling approach.....	16
2.2 Phase 1: Forecast LDC over the Long Term PASA Study Horizon	17
2.2.1 Developing the base year LDC.....	17
2.2.2 Scaling the base year LDC to forecasted values.....	17
2.3 Phase 2: Undertake Reliability Assessment.....	19
2.3.1 Fundamental market modelling.....	20
2.3.2 Monte Carlo simulation.....	21
2.3.3 Treatment of intermittent generation	24
2.3.4 Treatment of outages	25
2.4 Development of the Availability Curve	26
2.4.1 Determine MR 4.5.12(b).....	26
2.4.2 Determine MR 4.5.12(c)	29
2.4.3 Determine MR 4.5.10(e).....	29
2.5 Calculation of EDDQ	30
3 RESULTS.....	32
3.1 Reliability assessment.....	32
3.2 Availability Curve.....	33

3.3 Forecast EDDQ..... 36

APPENDIX A: ASSUMPTIONS 39

A.1 Capacity Credits..... 39

A.2 Intermittent Generation Assumptions 41

A.3 Planned and Forced Outage Assumptions 44

A.4 Demand assumptions 45

A.5 Network assumptions 49

A.6 Reserve Provision 51

1 INTRODUCTION

Australian Energy Market Operator (AEMO) has engaged Robinson Bowmaker Paul (RBP) to:

- Undertake the Reliability Assessment and Development of the Availability Curve for the Southwest Interconnected System (SWIS)
- Forecast the Expected DSM Dispatch Quantity (EDDQ) in accordance with clause 4.15.4A of the Wholesale Electricity Market (WEM) Rules and the Market Procedure: *Determination of the Expected DSM Dispatch Quantity and the DSM Activation Price*.

This report contains:

- Modelling methodology and assumptions
- Results of the modelling.

1.1 CONTEXT

AEMO is responsible for operating a Reserve Capacity Mechanism (RCM) to ensure that adequate supply is available over the long term. To assess the amount of reserve capacity that will be required the AEMO undertakes a Long term Projected Assessment of System Adequacy (Long Term PASA). The results of the Long Term PASA analysis feed into the AEMO's Statement of Opportunities (SOO) report which forecasts:

- The Reserve Capacity Target (RCT) (WEM Rule (MR) 4.5.10(b)) for each Capacity Year in the Long Term PASA study and the Reserve Capacity Requirement (RCR) (MR 4.6.1). The RCT is set so as to meet the Planning Criterion which is defined in MR 4.5.9. The Planning Criterion comprises two components:
 - A forecast peak component to ensure that adequate supply is available to meet a one in ten-year peak (MR 4.5.9(a)) and;
 - A reliability component to ensure expected energy shortfalls are limited to 0.002% of annual demand (MR 4.5.9(b)).
- Generation capacity and Demand Side Management (DSM) requirements in the form of the Availability Curve, which is defined by MR 4.5.12.

Additionally, MR 4.5.14A and 4.5.13(h) require AEMO to calculate and publish the Expected DSM Dispatch Quantity (EDDQ) for each Capacity Year in the Long Term PASA study.

The purpose of this exercise is to:

- Undertake a Reliability Assessment to ensure the RCT is compliant with MR 4.5.9(b) and
- Develop the Availability Curve defined by MR 4.5.12.
- Forecast the EDDQ defined by MR 4.5.14A.

1.2 SCOPE OF MODELLING

Our modelling covers:

- The Reliability Assessment for the 2018 Reserve Capacity Cycle covering Capacity Years 2018/19 to 2027/28
- The Availability Curve for the second and third year of the relevant Reserve Capacity Cycle, namely 2019/20 and 2020/21.
- The forecasted EDDQ for Capacity Years 2018/19 to 2027/28.

1.3 STRUCTURE OF THIS REPORT

The remainder of our report is structured as follows:

- Our modelling methodology is described in Chapter 2.
- Modelling results are summarised in Chapter 3.
- Key assumptions underpinning our modelling are summarised in Appendix A.

2 METHODOLOGY

2.1 OVERVIEW OF MODELLING APPROACH

The modelling for this project was undertaken in four phases as follows:

- *Phase 1: Forecast Load Duration Curves (LDC) over the Long Term PASA Study Horizon.* This involves forecasting LDCs over the Long Term PASA Study Horizon, taking into account the 50% Probability of Exceedance (POE) peak forecast and the expected annual demand forecast^{10,11}. The forecasted LDCs are a key input for Phases 2, 3 and 4.
- *Phase 2: Undertake Reliability Assessment.* This involves applying the second component of the Planning Criterion (MR 4.5.9(b)) to determine the amount of reserve capacity required to limit energy shortfalls to 0.002% of forecast annual demand for each Capacity Year in the Long Term PASA Study Horizon. This will enable AEMO to determine the RCT for each Capacity Year in the Long Term PASA Study Horizon. We have approached this task using a combination of fundamental market modelling and Monte Carlo (probabilistic) simulations to determine the percentage of forecast demand that would not be met due to unserved energy over the Long Term PASA Study Horizon.
- *Phase 3: Determine Availability Curve* for the second and third Capacity Years of the Long Term PASA Study Horizon. This phase involves:
 - Determining MR 4.5.12(b) and MR 4.5.12(c) and
 - Developing the two-dimensional duration curve required under MR 4.5.10(e).
- *Phase 4: Forecast Expected DSM Dispatch Quantity (EDDQ)* for the ten Capacity Years comprising the Long Term PASA Study Horizon for the 2018/19 Reserve Capacity Cycle. Our approach here is similar to the Reliability Assessment (using a combination of Monte Carlo simulations and fundamental market modelling). However, DSM dispatch is modelled more comprehensively to minimise the peak while meeting availability restrictions.

¹⁰ Provided by AEMO.

¹¹ MR 4.5.9(b) states that the Reserve Capacity Target should limit expected energy shortfalls to 0.002% of demand. In consultation with the IMO (in 2012) we have assumed that a reasonable interpretation of this is that the clause refers to an “average” or “expected” scenario. For this reason, we have used the 50% POE peak and expected energy demand to forecast LDC for the Reliability Assessment.

Each phase is described in further detail in the sections below.

2.2 PHASE 1: FORECAST LDC OVER THE LONG TERM PASA STUDY HORIZON

One of the key inputs to the Reliability Assessment and Availability Curve is the forecast LDC over the Long Term PASA Study Horizon. Our approach to forecasting the LDC has two components:

- *Developing the base year LDC:* First, load duration is developed using historical data. This is the LDC on which all forecasted LDCs will be based and
- *Scaling the base year LDC to forecasted values:* Forecasted load duration curves for each Capacity Year in the Long Term PASA Study Horizon are developed by scaling up the base LDC to match the 50% POE peak and expected energy forecast for the respective Capacity Year.

Each of the above bullets is described in more detail in the sections below.

2.2.1 Developing the base year LDC

The base year LDC is estimated by averaging LDCs over the last five Capacity Years (2012/13-2016/17). The advantage of this approach is that the averaging ensures that the base year LDC will be representative of recent history, while at the same time ensuring that more recent trends are captured with more recent data.

Figure 9 in Appendix A.4 summarises the historical LDCs alongside the average LDC (denoted by the dotted line) that we have used to undertake the recent reliability assessment.

2.2.2 Scaling the base year LDC to forecasted values

Having developed a base year LDC, we next scale the it to match the 50% POE peak forecast and expected demand in any given year.

In other words, for each Capacity Year of the Long Term PASA Study Horizon we require a forecasted LDC such that:

- The peak of the LDC equals the 50% POE peak forecast
- The load allocated across all hours sums to the expected demand forecast and

- The shape of the LDC should be "close" to the base year LDC developed above.

Before describing the LDC forecasting methodology it is important to note the following:

- First, the peak and energy demand forecasts are developed separately by AEMO's Forecasting Consultant. As such, there is no explicit relationship between the peak and energy demand forecasts.
- Second, the historical ratio of peak to average energy (approximately 1.8 in the last ten years) and forecasted peak to average energy ratio can be starkly different. For example, the forecasted ratios from 2012-2014 were in the region of 1.95-2.2, while from 2015-2017 ranged from 1.7-1.9.
- Hence, the "peakiness" envisaged by the forecasts may not necessarily be consistent with recent history. This means that based on these forecasts it is not possible to derive a forecasted LDC that exactly matches the base year LDC (as the base year LDC represents a peak to average energy ratio of around 1.8).

Given the above, we have defined a function $F(h)$ ($h \in$ hours of the year), such that the forecasted LDC for a given year t ($L\hat{D}C(h)$) can be derived by multiplying the average LDC ($\overline{LDC}(h)$) by this function. That is:

- $L\hat{D}C(h) = F(h) \times \overline{LDC}(h)$, such that:
 - $Max(L\hat{D}C(h)) = 50\%$ POE peak forecast in year t and
 - $\sum_{h=1}^{8760} L\hat{D}C(h) =$ Expected demand forecast in year t .

The function is defined to ensure that the shape of the LDC varies with differing peak/energy ratios in a way that is consistent with the historical LDCs of the last five years. Thus, we have defined $F(h)$ as follows:

$$F(h) = \begin{cases} \frac{p-z}{m^2}(m-h)^2 + z & \text{if } h \leq m \\ \frac{e-z}{(n-m)^2}(h-m)^2 + z & \text{if } h > m. \end{cases}$$

Where:

- p denotes the ratio of the 50% POE peak forecast to the five-year average peak demand
- e denotes the ratio of the expected hourly demand forecast to the five-year average hourly demand.
- m denotes the position in the LDC in which the curve flattens, as has been observed in the historical years. m is set to 3,000 hours from the observation of historical years.

- n denotes the total number of hours in a year and
- z represents a curvature constant that is adjusted to achieve the expected demand forecast in the resulting LDC.

As noted previously, the scaled LDCs are key inputs into both Phases 2 and 3. Specifically:

- They are used to project the hourly load in a forecast Capacity Year to be used for market modelling component of the Reliability Assessment.
- They are also used to derive the two-dimensional duration curve defined in MR 4.5.10(e), which is developed by adjusting further the scaled profiles (in Section 2.4.3) to incorporate the requirements of MR 4.5.10(e). This is addressed in further detail in Section 2.4 (Determine MR 4.5.10(e)).

2.3 PHASE 2: UNDERTAKE RELIABILITY ASSESSMENT

To assess the amount of reserve capacity required to limit energy shortfalls to the reliability criterion set by MR 4.5.9(b) (0.002% of annual demand) we use a combination of fundamental market modelling and probabilistic Monte Carlo simulations as follows:

1. For each Capacity Year of the Long Term PASA Study Horizon, we assume reserve capacity (generating capacity and DSM) equals the forecast peak quantity plus reserve margin and Load Following Ancillary Services (LFAS) quantity determined by MR 4.5.9(a).
2. Given our forecasted LDC (based on a 50% POE peak and expected demand growth, see Section 1.1.1), assumptions on the availability of intermittent generation (see below) and randomised outages (see below) we simulate the WEM using our proprietary modelling tool (WEMSIM - see below) over a large number of iterations. Each iteration will yield an estimate of unserved energy.
3. We then use the N iterations above to estimate EUE as follows:
 - $$EUE = \frac{1}{N} \sum_{i=1}^N \text{Unserved Energy}_i$$
4. We then calculate EUE as a percentage of annual demand.
5. If the percentage in Step 4 is less than or equal to 0.002% then we stop - the RCT will be set by the first component of the Planning Criterion (MR 4.5.9(a)).
6. If the percentage is greater than 0.002%, then:
 - We incrementally increase the reserve capacity (over and above the forecast peak quantity determined by MR 4.5.9(a)) and

- Repeat steps 1 to 6 until the percentage in Step 4 is less than or equal to 0.002%.

The above steps are a high-level summary of our modelling methodology for the Reliability Assessment. In the remainder of this section we provide the details around the specifics of the modelling. Specifically, the following sections outline how Steps 2 and 3 will be implemented in practice as follows:

- We first describe the tool we use to undertake the fundamental modelling of the Wholesale Electricity Market
- We then describe the methodology we use to undertake Monte Carlo simulations of the Wholesale Electricity Market and
- Finally, we describe the approach we use to treat intermittent generation and outages (which are inputs to the two components above)

2.3.1 Fundamental market modelling

The market simulation component of the Reliability Assessment is undertaken using the electricity market simulation tool (WEMSIM).

WEMSIM is an analytical dispatch planning and analysis tool that simulates the dispatch of thermal and other generation resources in a multi-regional transmission framework. WEMSIM is an optimization engine based on linear and mixed integer (MIP) programming. WEMSIM simultaneously optimises generation dispatch, reserve provision and, in MIP mode, unit commitment.

Figure 3: Overview of WEMSIM



WEMSIM requires inputs such as planting schedules, transmission information (limits, losses and outages), generator parameters (ramp rates, heat rates, outage rates, etc.) and LDCs.

In simulating the market, we run the market model a large number of times as indicated in Step 2 above (i.e. the Monte Carlo analysis), each time using a different random series for forced outages.

Our proposed approach to undertaking the Monte Carlo analysis and treatment of outages and intermittent generation is covered in the sections below.

2.3.2 Monte Carlo simulation

To derive an estimate of EUE (as required by MR 4.5.9(b)) it is necessary to estimate a probability distribution of unserved energy for each Capacity Year in the Long Term PASA Study Horizon. A single annual run of any fundamental market model will yield one estimate of unserved energy which is a single realisation from a probability distribution function. Hence, to estimate the EUE it is necessary to run the fundamental market model over a large number of iterations. Each one of these iterations will include probabilistically simulated forced outages and will produce one realisation of unserved energy (see Steps 2 and 3 above).

To produce a robust estimate of EUE a large number of iterations would be required. Here-in lies a computational problem: running a full market model (with hourly simulation and detailed transmission representation) over a significant number of iterations is very computationally intensive and cannot be undertaken in an efficient and timely manner.

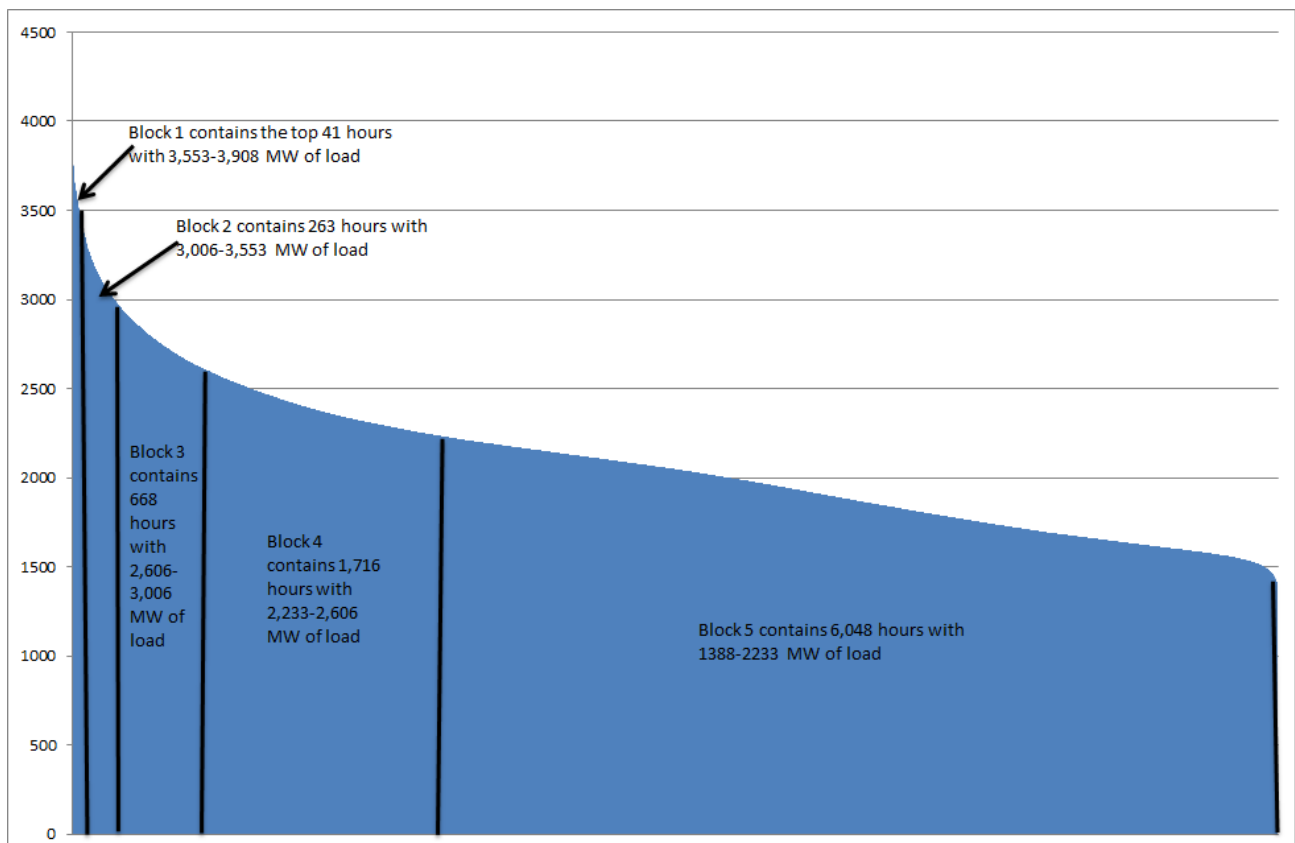
To this end, we have applied our previously employed non-sequential Monte Carlo methodology which combines market modelling and Monte Carlo analysis, by simulating the market in LDC blocks instead of undertaking full hourly runs.

Our approach is summarised below:

1. For each Capacity Year in the Long Term PASA Study Horizon we decompose the forecasted LDC into five discrete blocks of varying width. For example, the forecasted LDCs could be decomposed into 5 blocks at the following breakpoints: 90%-100% of peak load, 70%-90% of peak load, 50%-70% of peak load, 25%-50% of peak load and less than 25% of peak load. As an illustrative example, see Figure 4, which represents the forecasted LDC for the SWIS for the 2018/19 Capacity Year. Here:
 - The first block is the narrowest and contains peak hours pertaining to loads between 3,553 MW and 3,909 MW. Similarly, block 5 contains off-peak hours pertaining to loads between 1,388 MW and 2,233 MW.
 - The blocks are of varying width to reflect the homogeneity of system requirements in peak, peak/shoulder, shoulder and off-peak periods and to ensure sufficient granularity in those periods where unserved energy is most likely to occur (i.e. peak and shoulder periods).

- In each block b , we randomly sampled an hour N_b times (see Table 4 for illustrative sample sizes). The number of hours we sampled in each block was dependent on the likelihood of encountering unserved energy in that block. In the example in Figure 4:
 - Block 1 contains the 41 hours with the highest demand.
 - We randomly sampled from this block of 41 hours 4,500 times to get a sample S_{block1} such that: $S_{block1} \in \{s_1, s_2, \dots, s_{4500}\}$, and $S_{block1} \in \{\textit{The top 41 hours with the highest demand}\}$.
 - Unserved energy is most likely to occur in the first two selected blocks (the probability of unserved energy in the last three blocks will be negligible). For this reason, the first two blocks have the narrowest width and have the largest number of sampled hours to ensure we have greater statistical power for those hours where unserved energy is most likely.

Figure 4: Forecasted 2018/19 LDC decomposed into sampling blocks



2. We then run the market model (WEMSIM) for each sampled hour. WEMSIM dispatches plants based on load requirements (as determined by the random load pertaining to the sampled hour in the LDC), available generation (which will take into probabilistically simulated forced outages¹², availability of intermittent generation¹³ by season and planned outages¹⁴ as declared by market participants) and available DSM¹⁵. Each model run yields (for each sampled hour):
 - The amount of energy generated by each plant and
 - The quantity of unserved energy (if any).
3. Running the market model for each one of the sampled hours in a given block will yield a sample of unserved energy estimates pertaining to that block. This will enable us to estimate the EUE for the block by averaging over this sample and multiplying by the width of the block (to get MWh). Continuing with the Figure 4 example:
 - Block 1 (with sample $S_{block1} \in \{s_1, s_2, \dots, s_{4500}\}$), yields a sample of unserved energy estimates $UE_{block1} \in \{ue(s_1), ue(s_2), \dots, ue(s_{4500})\}$.
 - Block 1 has a width of 41 hours as it contains the 41 hours with the highest demand.
 - Therefore, the EUE for Block 1 (in MWh) would be estimated as follows: $EUE_{block1} = \frac{1}{4500} \sum_{i=1}^{4500} ue(s_i) \times 41$.
4. Repeating Steps 1 to 3 above for each block provides estimates for the EUE for all five blocks. We then calculate the EUE for the entire year by summing across the blocks as follows:

$$EUE_{year} = \sum_{i=1}^5 EUE_{block_i}$$
5. Steps 1 to 4 is repeated for each Capacity Year in the Long Term PASA Study Horizon to estimate the EUE for the relevant year.

¹² See Section 2.3.4 for details on how forced outages are modelled

¹³ See below in this Section for details on how intermittent generation is modelled

¹⁴ See Section 2.3.4 for details on how planned outages are taken into account

¹⁵ For the Reliability Assessment, DSM is modelled simplistically (as a generator of last resort with an artificially high short-run marginal cost), as the purpose here is to determine the aggregate level of Reserve Capacity required to satisfy the Planning Criterion. However, DSM is modelled in far greater detail in the determination of the Availability Curve (MR 4.5.12(b)) and EDDQ, taking into account the limitations around availability (see Section 2.4).

Table 4: Illustrative sample sizes for Monte Carlo analysis

Block	Breakpoint (% of peak load forecast)	Sample size (N_b)
1	90%	4,500
2	75%	3,000
3	60%	860
4	40%	250
5	25%	126

2.3.3 Treatment of intermittent generation

We adopt the following approach to modelling intermittent generation:

- Set seasonal profiles of existing intermittent plant by reviewing historical generation (including the most recently available data).
- Set seasonal profiles of new intermittent plant based on participant provided profiles or the profiles of existing intermittent plants of similar technology, size and location.
- Derate the intermittent plants based on the seasonal profiles above. The derated intermittent plants will be inputted into the fundamental market model in in Step 2 (Section 2.3, Monte Carlo simulation).

Solar generation is also modelled using historical and participant provided profiles. However, to accommodate the day/night profile of solar plants into our non-sequential Monte Carlo methodology, we have aggregated all solar facilities into one unit. In the section below, we describe our rationale for treating solar in this manner.

Approach to modelling solar generation

Modelling the seasonal and daily generation profiles of individual solar facilities is very computationally intensive when combined with the Monte Carlo approach described above. To ensure timely modelling results, we have aggregated all solar facilities into one facility for modelling purposes. This will produce prudent results for the following reasons:

- The profile of the aggregated solar unit is based on the individual profiles of each solar facility. Therefore, the generation of the aggregated unit in a given season will represent the sum of the generation of all individual solar units in the relevant season.

- We do not model transmission constraints. Therefore, the location of the solar facility will not affect our results.
- We have modelled the aggregated solar facility across a number of uniform units (where the number of units equals the number of solar facilities that are online in a given year). This means that in the event a solar unit is on forced outage¹⁶, only a fraction of solar generation is lost. Therefore, aggregating the solar facilities will not over-estimate the amount of generation lost in sampled period. Note that the amount of generation lost may be underestimated in some instances (i.e. if the largest solar facility were to lose all of its generation). However, as the forced outage rates of solar facilities are near zero, this is unlikely to have a material impact on the overall results.

2.3.4 Treatment of outages

There are two types of planned outages that can occur in the SWIS:

- Scheduled (or long-duration) outages
- Opportunistic maintenance (or short-duration outages).

When undertaking the fundamental market modelling described in Step 2 (Section 2.3, Monte Carlo simulation) we treat outages as follows:

- *Long duration outages.*
 - Generation facilities that provided information on long duration outages are taken out on the specified dates.
 - Generation facilities that have not provided information on long duration outages (undeclared long-duration outages) are seasonally derated based on historical planned outage information.
- *Opportunistic maintenance.* As in previous years we do not model opportunistic maintenance for the following reasons:
 - Opportunistic (day-ahead and on-the-day) maintenance are subject to System Management's evaluation process, whereby an outage will not be approved (and will even be recalled) if it violates the requirements in Section 3.18 of the Market Rules and
 - No planned outage would proceed in a period with a tight margin with a non-trivial risk of unserved energy.

¹⁶ Note that the probability that a single unit is on forced outage is very low (0.1%) (see Appendix A for forced outage assumptions).

Forced outages

The Monte Carlo analysis described above involves two stochastic variables:

- The load and
- The incidence of forced generation outages.

Load is randomised in the manner described in Step 1 (Section 2.3, Monte Carlo simulation).

Forced outages are randomised by:

- Determining a forced outage probability (FO_g) for each plant.
- Inputting these probabilities into the market model (in Step 2 (Section 2.3, Monte Carlo simulation)) which randomly assigns plant outages in a sampled hour based on the specified probability.

Where forced outage data is missing (e.g. for new plants) or inadequate (e.g. due to a small sample size of outages), our assumptions are based on available forced outage data of plants of a similar size, technology and age.

2.4 DEVELOPMENT OF THE AVAILABILITY CURVE

Having determined the RCTs for each Capacity Year, the next step involves assessing how much capacity is required for the two Availability Classes defined in the Market Rules to satisfy the targets for the second and third Capacity Years of the Long Term PASA Study Horizon as set out in Clause 4.5.12.

Additionally, clause 4.5.10(e) requires AEMO to develop a two-dimensional duration curve of the forecast minimum capacity requirements over the Capacity Year (“Availability Curve”) for each of the second and third Capacity Years of the Long Term PASA Study Horizon.

In this section, we outline the approach to determining the Availability Curve set forth in MR 4.5.12(b) and 4.5.12(c) and the two-dimensional duration curve set out in MR 4.5.10(e).

2.4.1 Determine MR 4.5.12(b)

MR 4.5.12(b) requires the determination of the minimum generation capacity requirement:

For the second and third Capacity Years of the Long Term PASA Study Horizon, AEMO must determine the following information:

b) the minimum capacity required to be provided by Availability Class 1 capacity if Power System Security and Power System Reliability is to be maintained. This minimum capacity is to be set at a level such that if:

- i. all Availability Class 2 capacity (excluding Interruptible Load used to provide Spinning Reserve to the extent that it is anticipated to provide Certified Reserve Capacity), were activated during the Capacity Year so as to minimise the peak demand during that Capacity Year; and*
- ii. the Planning Criterion and the criteria for evaluating Outage Plans set out in clause 3.18.11 were to be applied to the load scenario defined by clause 4.5.12(b)(i), then*

it would be possible to satisfy the Planning Criterion and the criteria for evaluating Outage Plans set out in clause 3.18.11, as applied in clause 4.5.12(b)(ii), using, to the extent that the capacity is anticipated to provide Certified Reserve Capacity, the anticipated installed Availability Class 1 capacity, the anticipated Interruptible Load capacity available as Spinning Reserve and, to the extent that further Availability Class 1 capacity would be required, an appropriate mix of Availability Class 1 capacity to make up that shortfall;

We calculate the minimum generation requirement by repeating the modelling exercise (for the second and third Capacity Years of the Long Term PASA Study Horizon) described in Section 2.3 with four differences:

- First, DSM is modelled in greater detail to take into account the constraints around the availability of DSM providers. In short, we allocate DSM throughout the year using an optimisation model that dispatches DSM to minimise the peak and subject to scheduling and availability constraints. See below for further details on our approach to modelling DSM.
- Second, we specify a Reserve Requirement in the market model that represents the ancillary services requirement of MR 3.18.11A (i.e. the Ready Reserve Standard, 520 MW¹⁷). We assume that only generation facilities that nominate themselves as reserve providers will provide reserve. This ensures that there is always a capacity margin equal to 520MW in any given hour.

¹⁷ Source: AEMO.

- Third, forced outages are taken out of the model, and the only stochastic component of the simulation is load. The reason for the removal of forced outages is that the specification of a reserve requirement on top of forced outages over-estimates the capacity margin. The purpose of the Ancillary Services Requirement is to cover unforeseen events such as forced outages. As such, if there were a forced outage in a given period, the operating reserve would be used to generate to prevent unserved energy. Hence, including forced outages and maintaining the Ancillary Services Requirement could lead to EUE exceeding 0.002% of annual demand.
- Finally, for each Capacity Year of the relevant Reserve Capacity Cycle, we iterate the model to reallocate the amount of DSM and generating capacity (keeping the total capacity capped at the RCT level) until the EUE requirement in MR 4.5.9(b) is violated.

The level of generation capacity at which the EUE equals 0.002% of expected demand sets the minimum generation capacity.

DSM Modelling Methodology

DSM in the Wholesale Electricity Market is subject to availability constraints. RBP forecasts hourly DSM dispatch by allocating available DSM throughout the year based on an optimisation model that takes into account the constraints above. Our approach is detailed further below:

1. Forecast sequential hourly load for the year using the methodology described in Section 2.2.
2. Use a spreadsheet-based optimisation model which, given the forecasted hourly load, dispatches DSM facilities (excluding Interruptible Load, as that is excluded under MR 4.5.12(b)) for each year to minimise the forecasted peak demand subject to the DSM's availability and dispatch constraints. The model performs the dispatch using a heuristic allocation method.
 - It should be noted that the nature of the problem of optimally allocating DSM is such that it would be computationally infeasible to guarantee that the result is the absolute optimum dispatch of DSM. The heuristic used will produce a dispatch that is close to optimal. We consider this to be acceptable, as the real-world dispatch of DSM is unlikely to be optimal either.
3. Adjust the LDC used in the market modelling by subtracting the forecasted DSM dispatch in the relevant hours (from Step 1 above). This adjusted LDC will represent the "effective demand" and be used in the derivation of the minimum generation capacity contemplated by MR 4.5.12(b).

Note that in this year's dataset, there were two DSM facilities projected to be certified and hold capacity credits across the Long Term PASA Study Horizon. Both these facilities are interruptible load facilities and are therefore excluded from the minimum generation capacity calculation. However, in undertaking the iteration to determine the minimum generation capacity calculation, we have to make assumptions about the availability of the hypothetical DSM facilities that we are simulating. In past years, we have used the availability characteristics of non-interruptible load facilities. This year, as there are no such facilities, we have assumed that the availability characteristics of the hypothetical DSM facilities we are simulating will be similar to the two interruptible load facilities that we have data for.

2.4.2 Determine MR 4.5.12(c)

MR 4.5.12(c) requires determining the capacity associated with Availability Class 2:

For the second and third Capacity Years of the Long Term PASA Study Horizon, AEMO must determine the following information:

c) the capacity associated with Availability Class 2, where this is equal to the Reserve Capacity Target for the Capacity Year less the minimum capacity required to be provided by Availability Class 1 capacity under clause 4.5.12(b).

This is a straightforward calculation that is computed by:

- Subtracting the minimum generation capacity, calculated above (see Section 2.4, Determine MR 4.5.12) from
- The RCT for the relevant Reserve Capacity Cycle (determined in Section 2.3).

2.4.3 Determine MR 4.5.10(e)

Clause 4.5.10(e) requires AEMO to:

develop a two-dimensional duration curve of the forecast minimum capacity requirements over the Capacity Year ("Availability Curve") for each of the second and third Capacity Years of the Long Term PASA Study Horizon. The forecast minimum capacity requirement for each Trading Interval in the Capacity Year must be determined as the sum of:

- i. *the forecast demand (including transmission losses and allowing for Intermittent Loads) for that Trading Interval under the scenario described in clause 4.5.10(a)(iv); and*
- ii. *the difference between the Reserve Capacity Target for the Capacity Year and the maximum of the quantities determined under clause 4.5.10(e)(i) for the Trading Intervals in the Capacity Year.*

Our interpretation of MR 4.5.10(e)(i) and the load scenario contemplated in MR 4.5.10(a)(iv) in deriving the LDC above was undertaken in consultation with the IMO and AEMO in previous years. Particularly, the approach above is predicated on the assumption that the difference between a 10% POE peak year and a 50% POE peak year (assuming expected demand growth) would only manifest itself in the first 24 hours (i.e. the peakiest part of the LDC). Hence, we model the forecast capacity requirement as a combination of the 10% POE peak LDC and 50% POE peak LDC (where these LDCs are derived in the manner described in Section 2.2.2).

Our approach to determining this quantity is summarised below.

1. Forecast the LDC for a given year as specified in MR 4.5.10(e)(i). To do this:
 - a. We estimate the forecast load in the first 24 hours assuming a 10% POE peak forecast and expected demand growth (i.e. the load scenario contemplated in MR 4.5.10(a)(iv)). This estimation will be undertaken using the scaling methodology described in Section 2.2.
 - b. We estimate the forecast load for the remaining hours (hours 25-8,760) hours assuming a 50% POE peak forecast and expected demand growth.
 - c. We use a smoothing function¹⁸ to smooth out the LDC in the first 72 hours.
2. Add the Reserve Margin and LFAS component of the MR 4.5.9(a) calculation (as provided by the AEMO) on top of the above LDC as required by MR 4.5.10(e)(ii) and

2.5 CALCULATION OF EDDQ

We forecast the EDDQ using the following approach:

- **Forecast EUE when DSM is dispatched for zero hours (EUE_{t_0}).** This involves repeating the Reliability Assessment as described in Section 2.3 but setting the available capacity of all DSM

¹⁸ We propose using a quadratic approximation to smooth the LDC.

facilities to zero. Hence, only generation capacity is available to meet demand as described in MR 4.5.14C(a).

- **Forecast EUE when DSM is dispatched for 200 hours ($EUE_{t,200}$).** This involves repeating the Step 1 above but with the forecasted LDC adjusted to take into account DSM dispatch for exactly 200 hours¹⁹. The optimised DSM dispatch is deducted off the forecasted LDC, and it is this adjusted LDC that becomes an input into the market model. Hence, generation capacity plus exactly 200 hours of DSM dispatch is available to meet demand as described in MR 4.5.14C(b).
- **Calculate EDDQ in year t** as follows:

$$EDDQ_t = \frac{EUE_{t,0} - EUE_{t,200}}{\text{Expected DSM Capacity Credits}_t}$$

¹⁹ Unlike the Minimum Generation Capacity modelling in Section 2.4.1, we have simulated the dispatch of the two Interruptible Load DSM facilities.

3 RESULTS

3.1 RELIABILITY ASSESSMENT

The Reliability Assessment indicated that for all Capacity Years of the Long Term PASA Study Horizon (2018/19 to 2027/28) the RCTs will be set by the forecast peak quantity determined by MR 4.5.9(a).

The EUE as a percentage of annual demand when total capacity is capped at the forecast peak component given by MR 4.5.9(a) (first column) is summarised in Table 5. Here we see that the peak forecast component is sufficient to limit expected energy shortfalls to 0.002% of annual demand in all years²⁰.

Table 5. Results of reliability assessment

Capacity Year	10% POE + Reserve Margin + LFAS requirement + IL Allowance	50% POE Peak Load (MW)	Expected demand (MWh)	EUE (MWh)	EUE as % of load
2018/19	4,553	3,909	18,304,209	8.1402	0.0000445%
2019/20	4,559	3,914	18,325,939	0.0000	0.0000000%
2020/21	4,581	3,928	18,416,128	0.0000	0.0000000%
2021/22	4,600	3,951	18,549,476	0.0635	0.0000003%
2022/23	4,626	3,983	18,707,347	2.5368	0.0000136%
2023/24	4,649	3,999	18,871,983	0.0617	0.0000003%
2024/25	4,677	4,024	19,096,597	0.9467	0.0000050%
2025/26	4,700	4,056	19,351,194	0.0000	0.0000000%
2026/27	4,730	4,082	19,641,783	0.0000	0.0000000%
2027/28	4,773	4,113	19,961,251	0.0126	0.0000001%

²⁰ Note that the 2018/19 and 2019/20 values in Table 1 do not replace the respective RCTs set in the 2017 WEM SOO.

Note that the highest unserved energy occurs in 2018/19 (although EUE as a percentage of expected demand is well short of 0.002%). The unserved energy in 2018/19 is a result of 200MW of thermal plants that are expected to be on outage in the first two weeks of August 2019²¹. Due to recent changes in load shape, there are now some high load periods in winter months. The combination of planned outages and high winter load result in unserved energy in August.

3.2 AVAILABILITY CURVE

The Availability Curves for Capacity Years 2019/20 and 2020/21 are summarised in Table 6 below. The load duration curves used to estimate MR 4.5.10(e) are illustrated in Figure 5 and Figure 6.

Table 6: Availability Curve, 2019/20 - 2020/21.

	2019/20	2020/21
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1		
Minimum capacity	3,919	3,946
MR 4.5.12(c): Capacity associated with Availability Class 2		
DSM	640	635

²¹ Based on information provided by market participants under MR 4.5.3.

Figure 5: Forecast capacity required, 2019/20

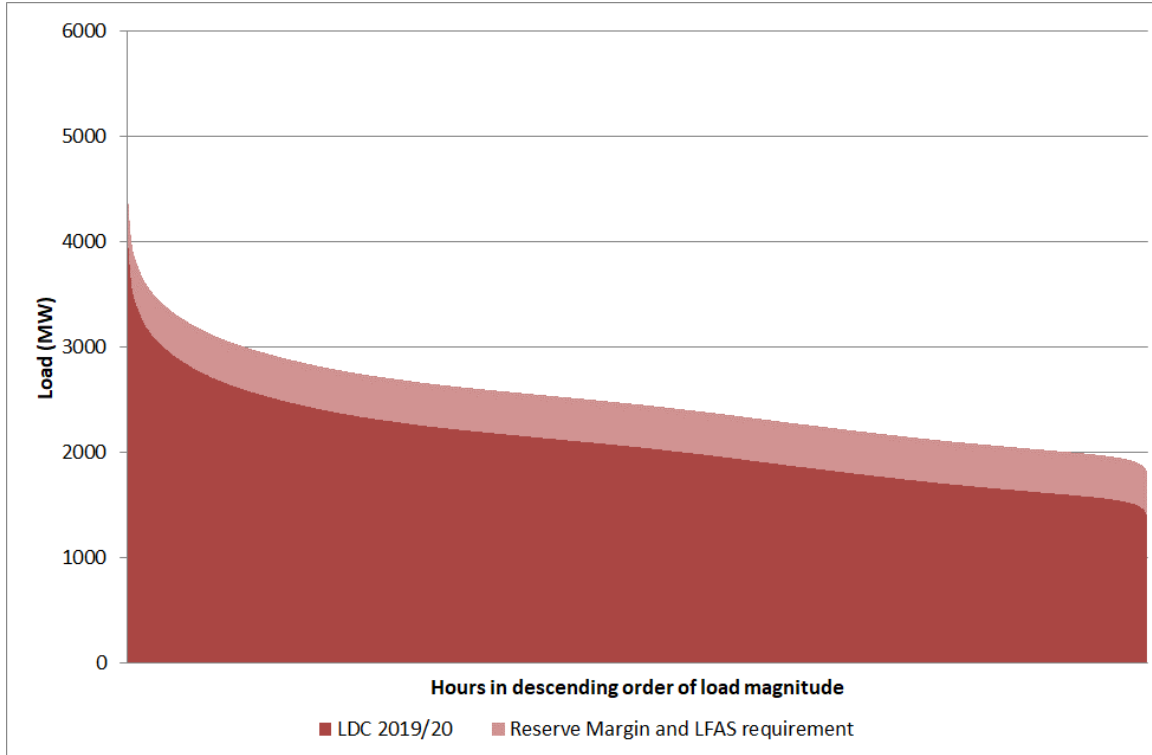


Figure 6: Forecast capacity required, 2020/21

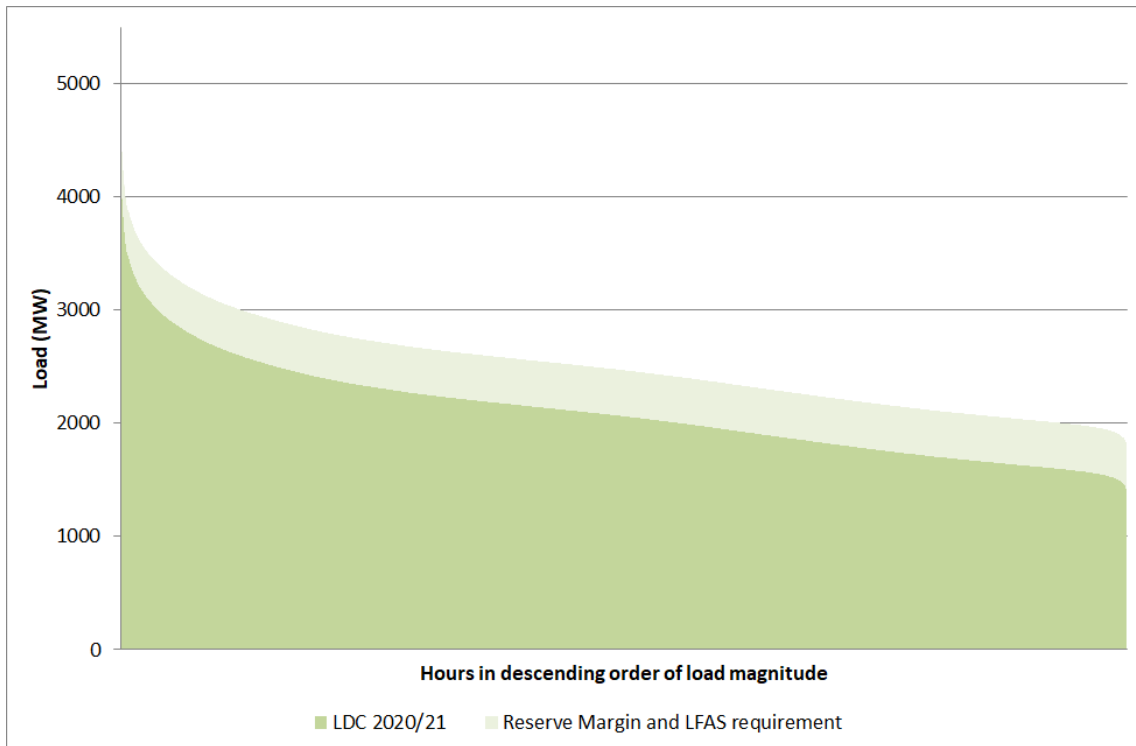


Table 7 compares the Availability Curve derived for the 2017 Long Term PASA to the current (Long Term PASA 2018) results. The 2017 Long Term PASA values are provided in parentheses.

Table 7: Comparing Long Term PASA 2018 Availability Curve to Long Term PASA 2017 Availability Curve (2017 results in parentheses)

2019/20	
MR 4.5.12(b): Minimum capacity required to be provided by Availability Class 1	
Minimum capacity	3,919 (3,823)
Reserve Capacity Target	
Reserve Capacity Target	4,559 (4,660)
MR 4.5.12(c): Capacity associated with Availability Class 2	
DSM	640 (837)

The capacity associated with Availability Class 2 (MR 4.5.12(c)) has decreased by 197MW since last year's Long Term PASA from 837MW to 640MW. This decrease is driven by:

- 900MW of thermal plants on outage in the first two weeks of October 2019²².
- The DSM optimisation model allocating hourly DSM to minimise the peak²³ subject to availability constraints. This means that most of the DSM is dispatched in the peakiest part of the LDC which occurs in the summer months (with some intervals in winter due to changing load shape). The model dispatches lower levels of DSM in October which is not enough to meet the net load with 900MW of scheduled generation on outage.
- The increased amount of solar in the capacity stack which means that in the evening (non-daylight) hours in October the amount of available generation decreases further.

²² Based on information provided by market participants under MR 4.5.3.

²³ In accordance with MR 4.5.12(b), the DSM optimisation model dispatches DSM facilities to minimise peak demand throughout the year (as opposed to maximising the operating reserve margin).

Note that while the RCT values in the 2018 Long Term PASA have decreased (compared with what was published in the 2017 Long Term PASA), this is not a driver for the decrease in the capacity associated with Availability Class 2. This is because, the decrease in the RCT has been offset by a corresponding decrease in peak and energy demand forecasts.

3.3 FORECAST EDDQ

The EDDQ results are summarised in Table 8. This also provides the resulting DSM Reserve Capacity Price (RCP) assuming an interim DSM Activation Price of \$33,460²⁴.

Table 8. EDDQ results

Capacity Year	EUE(t,0)	EUE(t,200)	CC(t)	EDDQ(t)	DSM RCP based on \$33,460 DSM Activation Price (MR 4.5.14F)
2018/19	19.9845	8.1402	57.426	0.2063	\$23,631.25
2019/20	0.9484	0.0000	66	0.0144	\$17,210.81
2020/21	0.0000	0.0000	66	0.0000	\$16,730.00
2021/22	0.8142	0.0635	66	0.0114	\$17,110.62
2022/23	4.8489	2.5368	66	0.0350	\$17,902.16
2023/24	0.5860	0.0617	66	0.0079	\$16,995.78
2024/25	2.3021	0.9467	66	0.0205	\$17,417.10
2025/26	0.1106	0.0000	66	0.0017	\$16,786.08
2026/27	0.0341	0.0000	66	0.0005	\$16,747.30
2027/28	1.1613	0.0126	66	0.0174	\$17,312.38

The highest EDDQ occurs in 2018/19 for the reasons noted in Section 3.1; namely the 200MW of scheduled generation expected to be on outage in the first two weeks of August combined with changing load shape leading to more high load periods in winter months.

EDDQ is otherwise low in most years. The reason is that unserved energy is very low under the reliability scenario to begin with (see Table 5). This, combined with the fact that there are only two

²⁴ As specified in Market Rule 4.5.14F; the DSM Activation Price represents the Value of Lost Load (VoLL).

facilities (with a combined CC assignment of 57.426 MW in 2018/19 and 66 MW in other Long Term PASA Capacity Years) means that not running these DSPs has a minimal impact on the level of unserved energy.

Figure 7 and Figure 8 compares the 2017 Long Term PASA EDDQ and DSM RCP to the 2018 Long Term PASA results.

Figure 7: Comparing 2017 and 2018 Long Term PASA EDDQ values

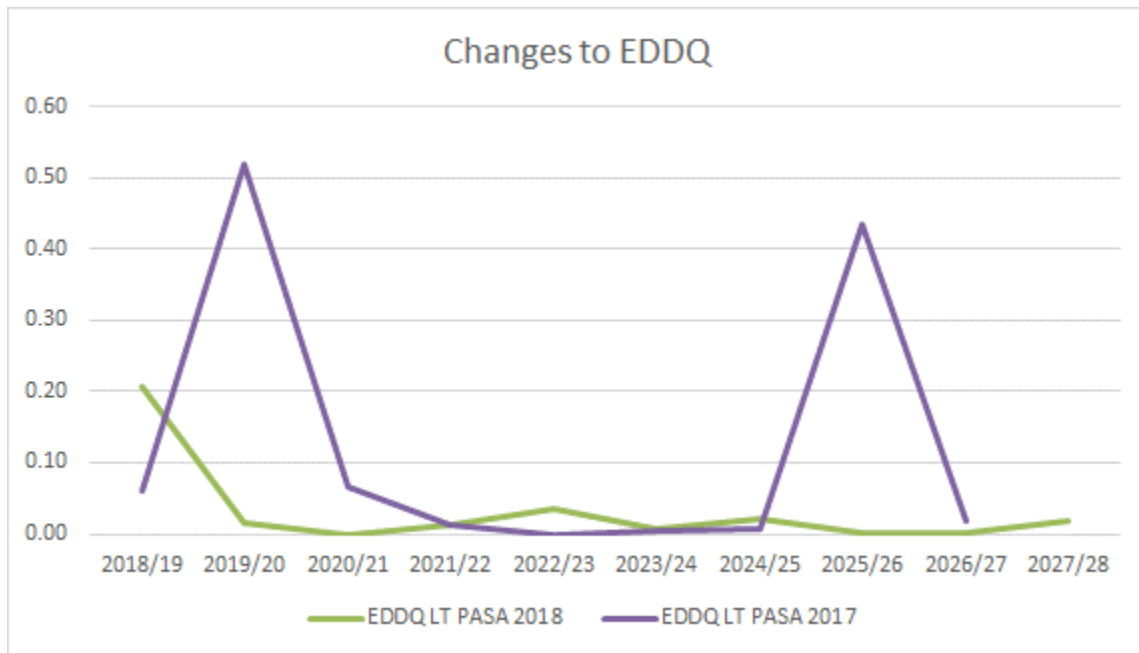
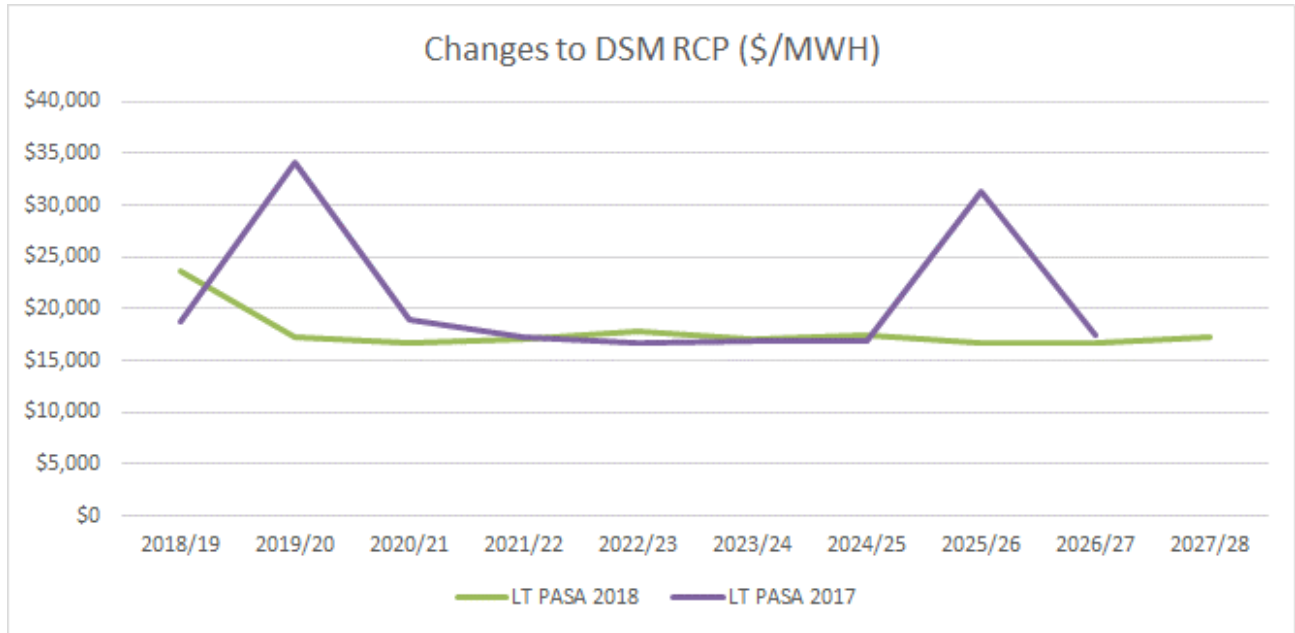


Figure 8: Comparing 2017 and 2018 Long Term PASA DSM RCP values



In the Long Term PASA 2017 dataset, the EDDQ and DSM RCP values were high in 2019/20 and 2025/26 due to a large scheduled generator forecast²⁵ to be on planned outage during the summer months. As there are no similar outages forecast in this year's dataset the EDDQ and DSM RCP have reduced and is relatively flat over the Long Term PASA Study Horizon (with the exception of 2018/19 - the reason for this peak is described above).

²⁵ Based on information provided by Market Participants under MR 4.5.3

APPENDIX A: ASSUMPTIONS

In this appendix we set out:

- Assumptions about Capacity Credits allocated to facilities over the Long Term PASA Study Horizon
- Intermittent generation assumptions
- Planned and forced outage assumptions
- Demand assumptions
- Network assumptions

A.1 CAPACITY CREDITS

As noted in Section 2.3, 1, for each Capacity Year of the Long Term PASA Study Horizon, we assume reserve capacity (generating capacity and DSM) equals the forecast peak quantity (including transmission losses and allowing for Intermittent Loads) plus reserve margin and Load Following Ancillary Services (LFAS) quantity determined by MR 4.5.9(a). To do this we pro-rate the capacity credit information (provided by the AEMO and Market Participants) for each facility were so that the total number of capacity credits in a given Capacity Year summed to the forecast peak component given by MR 4.5.9(a) for that Capacity Year as follows:

$$CC_{i_{adjusted}} = CC_i \times \frac{10\% \text{ POE peak} + \text{Reserve Margin} + \text{LFAS}}{\sum_{j \in \text{all facilities}} CC_j}$$

Note further:

- $\sum_{j \in \text{all facilities}} CC_j$ denotes the total unscaled capacity credits expected to be assigned to all facilities in a given year
- For scheduled generators and DSM facilities, CC_i is the value provided by AEMO and Market Participants
- For intermittent generation we assume CC_i to be equal to nameplate capacity multiplied by the average annual capacity factor (based on historical or participant provided data as relevant -

see Table 9)²⁶. Intermittent nameplate capacity (for wind and biogas plants) are back calculated so that $CC_{i_{adjusted}}$ (for intermittent plants) divided by the new nameplate capacity equals the relevant average annual capacity factor. Solar facilities are modelled by specifying seasonal generation limits which vary by time of day (see Section A.2 for more details).

²⁶ This will vary from the Relevant Level which is a function of generation during the hottest intervals of the hot season. For the purposes of the Reliability Assessment we are interested in the performance of the intermittent plant across the year so that we can get an estimate of EUE. Therefore, we use historical or participant provided profiles.

A.2 INTERMITTENT GENERATION ASSUMPTIONS

To model the intermittent nature of intermittent facilities, we have derated intermittent plants based on their seasonal profiles or capacity factors.

We have derived the derating factors or seasonal production profiles by:

- Reviewing historical intermittent generation for existing intermittent facilities and taking the average capacity factor (by season) over the last eight years.
- Using information provided by participants for new intermittent facilities.

We summarise our approaches to modelling wind/biogas and solar separately.

Wind and biogas

Seasonal profile assumptions for wind and biogas plants are summarised in Table 9 below. Each plant is assigned a seasonal capacity factor which is applied to the scaled nameplate capacity described in Section A.1. Particularly, in a given Capacity Year for a given wind or bio-gas plant, we perform the following steps:

1. Calculate average annual (Ann_{CF}) AND seasonal capacity factors (CF_s , $s \in \{\text{summer, autumn, winter, spring}\}$) as follows:

$$Ann_{CF} = \frac{\text{Historical Generation (MWH)}}{\text{Nameplate Capacity} \times \text{Hours in Historical Period}}$$

$$CF_s = \frac{\text{Historical Generation}_s(\text{MWH})}{\text{Nameplate Capacity} \times \sum_{h \in \text{historical period}} \text{Hours}_{s,h}}$$

2. Calculate unscaled average generation to be attributed to INTMT_FAC (UnscaledGen_{INTMTFAC}):

$$\text{UnscaledGen}_{\text{INTMTFAC}} = \text{NamePlate}_{\text{INTMTFAC}} \times Ann_{CF}$$

3. Calculate scaled average generation to be attributed to INMT_FAC (ScaledGen_{INTMTFAC}) so that the CCs summed over all facilities add up to the RCT:

$$ScaledGen_{INTMTFAC} = UnscaledGen_{INTMTFAC} \times \frac{10\% POE\ peak + Reserve\ Margin + LFAS}{\sum_{j \in all\ facilities} CC_j}$$

4. Back-calculate the nameplate capacity ($NamePlate_{INTMTFAC,scaled}$) so that if we apply Ann_{CF} we get $ScaledGen_{INTMTFAC}$.

$$NamePlate_{INTMT,Scaled} = \frac{ScaledGen_{INTMTFAC}}{Ann_{CF}}$$

5. In the market model, specify:
- Maximum Capacity of INTMTFAC to be $NamePlate_{INTMT,Scaled}$
 - Set the number of units in season s ($unit_s$) so that $unit_s = CF_s$
 - Given a and b: $\sum_{s \in seasons} NamePlate_{INTMT,Scaled} \times CF_s \times Hours_s = ScaledGen_{INTMTFAC}$

For new wind plants Ann_{CF} and seasonal capacity factors (CF_s) are calculated using participant provided generation figures by season and nameplate capacities.

Table 9 summarises the average seasonal capacity factors of wind and biogas plants. Note that in the market model we have model facilities separately using facility specific seasonal capacity factors.

Table 9: Seasonal profiles for intermittent generation (wind and biogas)

Facility	Spring	Summer	Autumn	Winter
Wind	34.94%	38.11%	30.92%	33.57%
Biogas	74.88%	81.67%	66.26%	71.93%

Solar profiles

Solar generation is modelled as an aggregated facility whose seasonal generation is assumed to be the sum of the seasonal generation of individual solar facilities. Solar plants are also derated to zero during non-daylight hours. Daylight hours are assumed to be:

- 05:00 - 18:30 (inclusive) in spring and summer
- 06:00 - 17:30 (inclusive) in autumn and winter

We have modelled solar as follows:

- Based on production profiles provided by participants (for all new solar plants) and historical generation data (for Greenough_River_PV1) we estimated daytime generation (MWH) for each solar facility by season.
- We summed the facility specific generation to obtain seasonal daytime generation for the aggregated solar plant (ALL_Solar).
- In any given Capacity Year, the above estimated generation is scaled down by the capacity credit scaling factor described in Section A.1²⁷ so that the capacity credits allocated to all facilities sum to the peak forecast component in clause 4.5.9(a) of the WEM Rules.
- ALL_Solar’s generation is spread across a number of uniform units, where the number of units equals the number of solar facilities that are operating in a given Capacity Year. This ensures that in the event of a forced outage, only a fraction of solar generation is lost.

Table 10 summarises our assumptions on the number of units associated with ALL_Solar and the assumed generation of each unit. The number of units and scaled MW values in this table (in parentheses) are what is used in the market modelling.

Table 10: Average hourly generation of ALL_Solar units during daylight hours (scaled generation (used in the market model) is in parentheses)

Year	Number of units	Average hourly generation per unit during daylight hours (MW)			
		Spring	Summer	Autumn	Winter
2018	3	3.592 (3.306)	4.202 (3.867)	3.501 (3.222)	2.749 (2.53)
2019	5	18.589 (16.959)	21.182 (19.324)	16.816 (15.341)	12.652 (11.542)
2020	10	26.338 (23.206)	30.204 (26.612)	22.005 (19.388)	17.809 (15.691)
2021	10	26.338 (22.18)	30.204 (25.436)	22.005 (18.531)	17.809 (14.997)
2022	10	26.338 (22.307)	30.204 (25.581)	22.005 (18.637)	17.809 (15.083)
2023	10	26.338 (22.415)	30.204 (25.705)	22.005 (18.728)	17.809 (15.156)

²⁷ Scaling factor equals $\frac{10\% \text{ POE peak} + \text{Reserve Margin} + \text{LFAS}}{\sum_{j \in \text{all facilities}} CC_j}$

Year	Number of units	Average hourly generation per unit during daylight hours (MW)			
		Spring	Summer	Autumn	Winter
2024	10	26.338 (22.551)	30.204 (25.861)	22.005 (18.841)	17.809 (15.248)
2025	10	26.338 (22.444)	30.204 (25.738)	22.005 (18.752)	17.809 (15.176)
2026	10	26.338 (22.586)	30.204 (25.901)	22.005 (18.87)	17.809 (15.271)
2027	10	26.338 (22.795)	30.204 (26.141)	22.005 (19.045)	17.809 (15.413)

A.3 PLANNED AND FORCED OUTAGE ASSUMPTIONS

Planned outages

Outages are modelled as follows:

- Where participants have provided information on future planned long duration outages²⁸, we have taken facilities out on the specified dates.
- We have reviewed AEMO’s real time outages data set to validate some of the data provided above, and to include long duration outages (greater than 2 days) that were missing in the data set above.
- For facilities that have no planned outages provided in the two datasets above, we have reviewed historical planned outage rates to determine whether they need to be derated to reflect maintenance. We have derated only one facility as the vast majority of facilities that have no planned outages listed in the data above have historical planned outage rates²⁹ of close to 0%.

²⁸ Based on information provided by market participants under MR 4.5.3.

²⁹ Over the last ten years

Forced outages

Forced outage rates are based on the historical ten year average for existing plants. For new plants we have assumed forced outage rates will be similar to new plants of a similar technology.

A.4 DEMAND ASSUMPTIONS

In this section, we set out:

- RCT and demand forecasts
- The base year load duration curve which is used as a basis to forecast load shape and hourly load over the Long Term PASA Study Horizon
- Regional load participation factor assumptions

RCT and demand forecasts

Table 11 summarises:

- The peak forecast component of clause 4.5.9(a) of the WEM Rules (which has set the RCT in every Capacity Year of the Long Term PASA Study Horizon)
- The 50% and 10% POE peak demand forecasts (expected scenario)
- The annual demand forecast (expected scenario).

Table 11: RCT and demand forecasts

Year	Peak forecast component of Planning Criterion MR 4.5.9(a)	50% POE peak forecast	10% POE peak forecast	Expected Annual Demand (MWH)
2018/19	4,553	3,909	4,146	18,304,209
2019/20	4,559	3,914	4,152	18,325,939
2020/21	4,581	3,928	4,174	18,416,128
2021/22	4,600	3,951	4,193	18,549,476
2022/23	4,626	3,983	4,219	18,707,347
2023/24	4,649	3,999	4,242	18,871,983
2024/25	4,677	4,024	4,270	19,096,597

Year	Peak forecast component of Planning Criterion MR 4.5.9(a)	50% POE peak forecast	10% POE peak forecast	Expected Annual Demand (MWH)
2025/26	4,700	4,056	4,293	19,351,194
2026/27	4,730	4,082	4,323	19,641,783
2027/28	4773	4,113	4,365	19,961,251

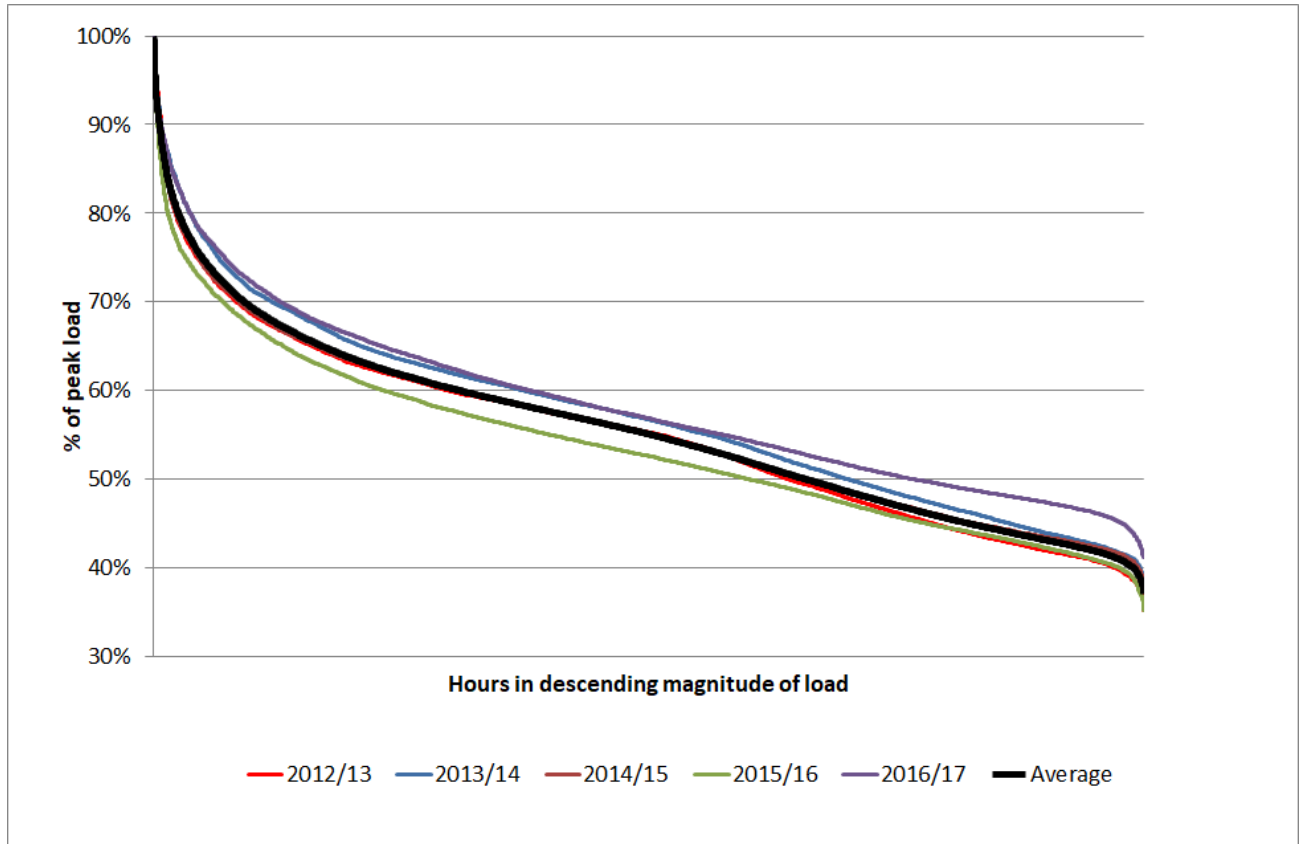
Base year load duration curve

We use the TT30GEN dataset from AEMO’s website to calculate historical hourly load. Additionally:

- NLMQ values for Greenough River and Mumbida (provided by AEMO) are added on as these are excluded from the TT30GEN dataset
- Curtailments (due to generation shortfall, provided by AEMO) are also added on to get gross load.

The base year load duration curve and the load duration curves for the past five Capacity Years are summarised in the figure below. The base year load duration curve is denoted by the 5 year average (i.e. the black dotted line).

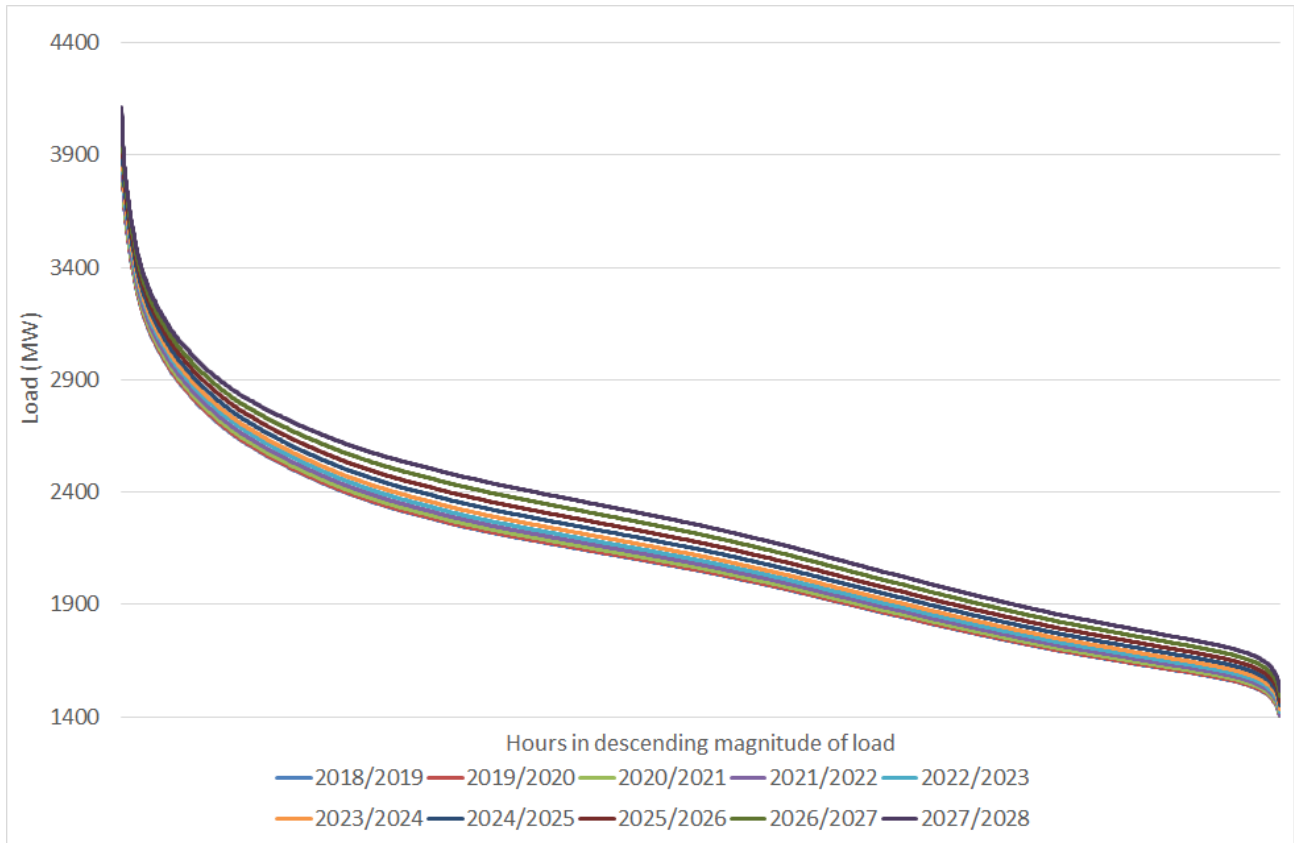
Figure 9: Base year load duration curve



Forecasted Load Duration Curves

Figure 10 summarises the forecasted load duration curves that we have used in our market simulations. These load duration curves are developed by applying the methodology in Section 2.2.2 to the base year load shape from Figure 9 and the peak and energy demand forecasts from Table 11.

Figure 10: Forecasted Load Duration Curves for Capacity Year 2018/19 to 2027/28 (50% POE peak demand and expected energy demand)



Load participation factors

Load participation factors are calculated using peak load distribution across regions (as provided by Western Power).

Table 12: Regional load participation factors

Year	North	Perth	East	South
2018	4.8%	74.5%	7.0%	13.6%
2019	4.8%	74.0%	7.1%	14.1%
2020	4.7%	73.8%	7.2%	14.3%
2021	4.7%	73.7%	7.1%	14.4%
2022	4.7%	73.6%	7.2%	14.5%
2023	4.7%	73.4%	7.2%	14.7%
2024	4.7%	73.3%	7.2%	14.8%
2025	4.7%	73.2%	7.2%	14.9%
2026	4.7%	73.1%	7.3%	15.0%

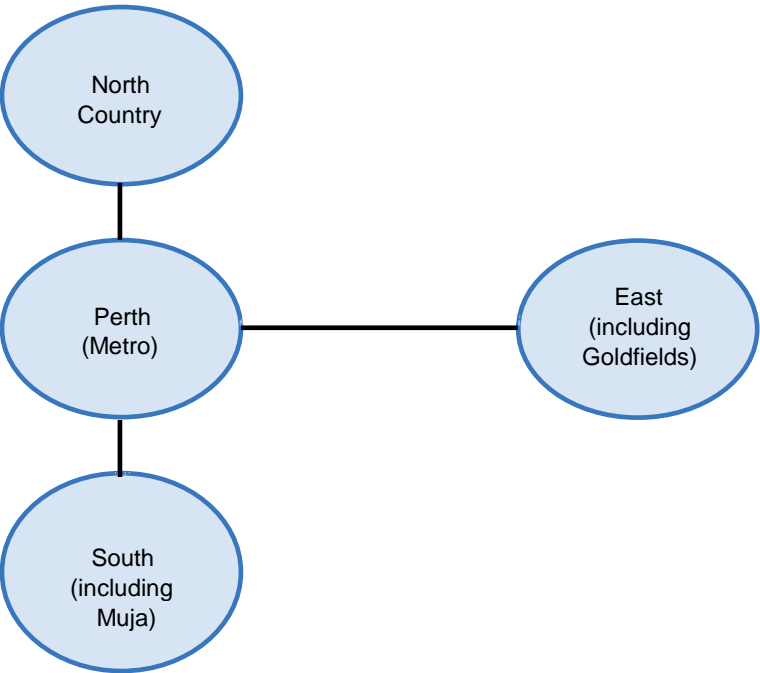
Year	North	Perth	East	South
2027	4.7%	72.9%	7.3%	15.1%
2028	4.7%	72.8%	7.3%	15.2%

A.5 NETWORK ASSUMPTIONS

Topography

Four regions (or nodes) are represented in the market model as illustrated in Figure 10 below.

Figure 11: Network topography



Network constraints

No line constraints are modelled on instruction from the AEMO as Western Power has implemented various measures to manage localised constraints, outside of the RCM, such as:

- Offering curtailable access to new loads that wish to connect to the grid in “constrained” regions. For example, any new load wishing to connect in the Goldfields will be provided an access contract that mandates that the load be curtailed under certain conditions and
- Network Control Services (NCS). Western Power is currently seeking to procure NCS capacity as an alternative to, or to allow deferral of, network investment.

Losses

No losses are modelled for transmission lines as peak and total demand forecasts were calculated on a "generation sent-out basis". The inclusion of losses in the demand forecasts are such that they cannot be separated from the final forecasts. As such line losses are not included in the model.

A.6 RESERVE PROVISION

As noted in Section 2.4.1, the minimum generation capacity requirement prescribed by MR 4.5.12(b) is modelled by assuming a reserve requirement equivalent to the Ready Reserve Standard defined in MR 3.18.11A.

The Ready Reserve Standard is incorporated into the market model to ensure that at any given time, there is enough available capacity to meet the capacity margin envisaged by the standard. In other words, the model will:

- Dispatch facilities to meet load **and**
- Hold in reserve enough facilities so that there is at least a 520MW capacity margin (Available generation less Load).